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REVIEW

Model-aided learning for adaptive management of natural resources: an evolutionary design perspective

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Summary

1. Researchers using the adaptive management paradigm consider learning about the behaviour of social-ecological systems as an inherent element of endeavours to improve the provision of ecosystem services. Learning-by-experience about social-ecological systems is a slow process attributable to system complexity. We review recent developments in systems modelling which support learning by creating a salient diversity of management alternatives and by translating science-based results into stakeholder perspectives.

2. Design-oriented learning cycles aimed at developing ecosystem services could be improved using systematic model-based diversification and selection of natural resource management alternatives.

3. Recent advances in spatially explicit computer-based ecological modelling and in visualization of results can effectively support repeated learning cycles.

4. Prioritization and weighing of conservation objectives and ecosystem services should be postponed until after the exploration of the synergies and trade-offs among objectives.

5. Investigating whether this evolutionary design approach can increase adoption of management adjustments and help to avoid lock-in onto unsustainable development trajectories should be part of efforts to understand the way we learn.

Key-words: adaptive management, multicriteria decision-making, multi-objective optimization, Pareto-based ranking, solution space

Introduction

Integrated assessments have alerted global society to the deplorable state of natural resources in many parts of the world (Kiers *et al*. 2008). At the same time, the size of the human ecological footprint (MA (Millennium Ecosystem Assessment) 2005; Steinfeld *et al*. 2006; UNEP (U.N. Environment Programme) 2007; IPCC (Intergovernmental Panel on Climate Change) 2007) continues to increase because of the over-exploitation and deterioration of resources and ecosystem services (Carpenter *et al*. 2009). A major challenge for humanity is to learn how to organize itself to reverse these negative trends and to effectively deal with the common pool character of many natural resources (Ostrom *et al*. 1999; Scheffer, Brock, & Westley 2000). Such efforts can draw on extensive scientific analyses of natural resource governance accumulated over the past decades (Dietz, Ostrom, & Stern 2003), which highlight the complexity arising from interactions among multiple actors, multiple levels of organization and multiple objectives and the failures arising from not dealing with these effectively (Ostrom 2007; Walters 2007).

Problems in natural resource management (NRM) are typically ill-structured because both goals of management and knowledge underpinning decisions are contested (Hisschemöller & Hoppe 1995). Participatory processes serve to delineate the problem and to frame the management options in terms of the perspectives of the various actors (Bouwen & Taillieu 2004). The contribution of science to solving NRM problems may be defined as bringing together existing knowledge from diverse sources into new perspectives for systems management (Folke *et al*. 2005). Opinion converges that a control-oriented systems management perspective is not effective in NRM (Holling & Meffe 1996) because the inherent uncertainty of the complex systems and their emergent properties make linear planning futile. Adaptive management, in which

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policies and system interventions are seen as experiments that need to be continuously monitored, updated and adjusted, provides an alternative paradigm (Gundersson, Holling, & Light 1995). Essential features in adaptive management are processes that generate learning, meaning, knowledge and experience of ecosystem dynamics (Folke *et al.* 2005).

Quantitative systems models constitute an important means of learning. They help by providing insight into important processes and drivers of systems behaviour, thus contributing to meaning and knowledge. Scientific and policy-oriented research relies on this use of system models from molecular (Kitano 2002) to global (IPCC (Intergovernmental Panel on Climate Change) 2007) levels. Models are also used to structure thinking about implications of system configurations that do not yet exist, thus supporting design (Lovell & Johnston 2009). This use of models is, for instance, a common practice in evaluating national economic policies in many countries; in the European Union, ex-ante impact assessment is a mandatory element of new policies (EC (European Commission) 2005). Finally, if transparent, models support communication on assumptions about system processes. Here, we review the role of learning in NRM projects and show how design-oriented quantitative systems modelling can enhance learning by diversifying the solution space, revealing trade-offs and synergy among objectives, and supporting selection of 'fit' alternatives.

NRM and learning

Projects that aim to improve NRM and to foster the provision of ecosystem services are usually structured in several phases (e.g., Margules & Pressey 2000; Van Noordwijk, Tomich, & Verbist 2001; Peterson, Cumming, & Carpenter 2003; Giller *et al.* 2008; Lovell & Johnston 2009; Grantham *et al.* 2010), derived from the classical steps of the problem-solving or experiential learning cycle (cf. Kolb 1984): (i) problem definition: delimitation of the landscape or land-use system to be managed, and describing goals and indicators, (ii) diagnosis: analysis of the existing situation, (iii) exploration: development and evaluation of alternatives, (iv) redesign: selection and elaboration of the most desirable alternative and, finally, (v) implementation of this alternative aided by suitable policies, including monitoring. In each of these phases, iteration or feedback to previous phases may take place when more knowledge becomes available. An important pitfall in this approach is an early convergence on a limited number of alternatives during exploration of alternative options. While this allows keeping things manageable for project managers and participants, it biases discussion and limits the potential to learn from the project.

The efficacy of the problem-solving cycle can increase considerably if more attention is paid to the systematic creation of a large diversity of alternatives to choose from (Van Noordwijk, Tomich, & Verbist 2001; Page 2007) in step (iii) and if informed selection of the most desirable alternative for implementation is facilitated in step (iv), after the room to manoeuvre has been explored and discussed. To emphasize the importance of iteration of (parts of) the problem-solving cycle and the role of diversification and selection to support learning, we designate this enhanced problem-solving cycle as an evolutionary design cycle. Heuristic optimization techniques such as evolutionary algorithms (EAs), with Pareto-optimality as a selection criterion and multicriteria methods to link supply and demand of ecosystem services, provide underutilized methodological tools to support this evolutionary design cycle. These approaches are described in the next sections.

Creating diversity

Exploration of NRM alternatives is often based on a small number of 'sketch designs' – scenarios developed by experts or in participatory settings with stakeholders (e.g., Peterson, Cumming, & Carpenter 2003; Dockerty *et al.* 2006; Bohnet & Smith 2007; Nelson *et al.* 2009). This approach is similar to the way architects work when designing buildings, parks or gardens. Although more cumbersome, systematic generation of a large set of alternatives that perform differently in terms of the various ecosystem services has three major advantages over the sketch design approach. Firstly, the interactions among ecosystem services can be explored and trade-offs made apparent (Groot *et al.* 2007; Tittonell *et al.* 2007; Groot, Jellema, & Rossing 2010). This gives insight into the scope for manoeuvre given the various and often conflicting objectives of the stakeholder groups involved. Secondly, psychology research on self-determination and motivation (Ryan & Deci 2000) has shown that acceptance and internalization of policy solutions is enhanced if decision-makers are offered a choice from a broad portfolio of alternatives because this supports their sense of having autonomous choice as opposed to policy prescription (Moller, Ryan, & Deci 2006). Thirdly, exploration of the full solution space (Wiek & Binder 2005) can yield radically different alternatives that can break path-dependency and avoid lock-in onto suboptimal solutions, which can occur when only small incremental changes are implemented (Kirk, Reeves, & Blackstock 2007). Heuristic optimization techniques can assist in creating the desired salient diversity in alternatives for resource management.

Stakeholders in NRM projects typically state a range of ambitions, interests and perspectives regarding the provision of ecosystem services and NRM can thus be considered a multi-objective optimization problem. Land-use activities constitute the decision variables which determine the provision level of the objectives representing the salient ecosystem services (Fig. 1a). In contrast to global, single-objective optimization, multi-objective problems do not have a single optimal solution, but are solved by a set of alternative solutions that reveal synergies or trade-offs among the objectives (Coello Coello, Lamont, & Van Veldhuizen 2007). A considerable part of multi-objective optimization procedures rely on aggregating the various objectives into one by weighing and normalization and then optimizing a single-objective problem. Weighing procedures, however, introduce technical complexity and arbitrary choices that are not conducive to the transparency of NRM design processes where conflict and negotiation usually

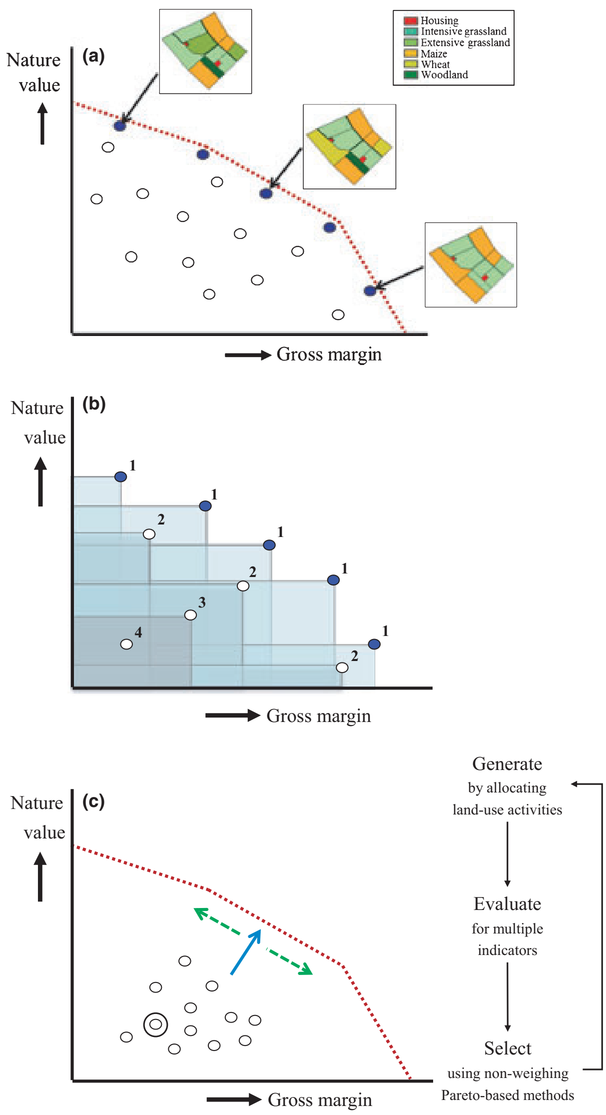

Fig. 1. (a) Stylized illustration of a trade-off between farm gross margin and nature value in an agro-ecosystem, and associated landscape maps for three alternatives. The closed symbols represent landscape alternatives belonging to the Pareto-optimal set (i.e. having rank 1). The ranking scheme is demonstrated in (b), where the shaded areas indicate the region of the solution space that is dominated by the solution located at the top-right corner: the solution outperforms all other solutions within the shaded area for each objective (for further explanation see text). (c) Conceptual outline of the optimization process employing the iterative steps of generating, evaluating and selecting (right side) and in the graph the pressures exerted by the optimization algorithm through Pareto ranking (solid arrow, blue) and the search for less crowded areas (dashed arrows, green) are indicated. The encircled solution may represent the original situation. The dotted line in (a) and (c) indicates the Pareto frontier, which is approached by the evolutionary optimization algorithm.

prevail. Pareto-optimality represents a powerful criterion to combine objectives without *a priori* weighing that has been scarcely used thus far. The Pareto-optimal solution set is a collection of alternatives that cannot be improved for one of the objectives without compromising any of the other objectives involved (Fig. 1a). Put differently, the alternatives in the Pareto-optimal set are not 'dominated' by solutions that perform better for all the objectives (Fig. 1b). In a set of alternatives comprising both optimal and nonoptimal solutions, the dominance concept can be used to rank the alternatives in terms of Pareto-optimality in different ways (Coello Coello, Lamont, & Van Veldhuizen 2007). For example, after removal of the nondominated alternatives (rank 1) from the set, a new collection of nondominated alternatives can be identified that will receive rank 2 (Fig. 1b). This can be repeated until all alternatives have been ranked (Goldberg 1989). In this way, the initial *n*-dimensional optimization problem is reduced to a one-dimensional problem without *a priori* weighing.

Broadly speaking, multi-objective optimization may be achieved through exact methods from the domain of mathematical programming or by approximation with heuristic optimization techniques. Mathematical programming includes a wide range of optimization methods among which linear programming (LP) and dynamic programming (DP) probably have been applied most in agro-ecology (e.g. Hazell & Norton 1986; Kaiser & Messer 2011). Each method requires a specific formulation of the problem to be optimized. LP requires a single-objective function which is optimized subject to a (large) number of mathematical constraints. Both objective function and constraints are linear combinations of decision variables, which may be continuous (e.g. number of hectares under a particular land use) or integer (e.g. number of animals). Algorithms are available to find the values of the decision variables that maximize or minimize the objective function while satisfying the constraints. Uncertainty and risk can be taken into account both in the objective function to represent risk behaviour of the decision-maker, and in coefficients as is done in stochastic LP (reviewed by Luhandjula 2005). In DP, the problem is split up into a number of stages. At each stage, the system is represented by one or more state variables. States at one stage evolve into the next stage based on decisions, each of which affects the so-called value function, representing knowledge of system behaviour. A recursive algorithm, which starts from the last stage and progresses to the first, finds the maximum or minimum value of the value function for each of the states. The final step is to find the associated decision sequence in a forward calculating mode, starting from the current state of the system. Uncertainty in both state and value function is taken into account in stochastic DP. Recently, a substantial body of literature has used stochastic DP techniques under the name of Markov decision processes to explore optimal management of natural resources. For reviews see Williams (2009) and Mackenzie (2009). All mathematical programming techniques theoretically find the optimal solution, although in practice the calculation time is a serious constraint. In DP this problem is known as the 'curse of dimensionality'; also integer LP problems face these constraints.

Genetic algorithms (GAs) or EAs belong to heuristic optimization techniques. GAs and EAs are adaptive search techniques based on the principles of natural evolution. Genetic operators for reproduction, selection, mutation and crossover (the latter only in GAs) are applied to a set of solutions to improve its average performance criteria generation by

generation (Bergey & Ragsdale 2005). The absence of guaranteed convergence on optimal solutions, as in mathematical programming, is counterbalanced by the absence of the need to drastically reformulate and simplify the model structure (Coello Coello, Lamont, & Van Veldhuizen 2007). Evolutionary algorithms improve an initial set ('population' in jargon) of alternatives in repeated cycles of generation of new alternatives, evaluation of the generated alternatives in terms of the objectives, and selection of most desirable alternatives for a next generation (Fig. 1c). New alternatives can be generated by changing resource management in existing solutions randomly, deliberately or by perturbation and recombination of existing alternatives. Each alternative is then evaluated in terms of the objectives that represent relevant ecosystem services. Evaluation may involve application of static or dynamic disciplinary models, pertain to one or several spatial and temporal scales, and can be carried out assuming stable conditions or uncertainty and environmental change. Methods to quantify indicators and the related data sources can be quite heterogeneous, ranging from survey, monitoring or experimental data, established empirical relations, or calibrated and validated computer simulation models, to expert knowledge and rules of thumb. Which type of quantification is most appropriate depends on the amount of knowledge available, the demands of the involved stakeholders and the status of the project. Once the evaluation is completed for each of the objectives, the population is ranked using the Pareto-optimality criterion and the best performing solutions are selected. Selection of the solutions may be entirely based on Pareto-rank or may use additional criteria such as the distance between the

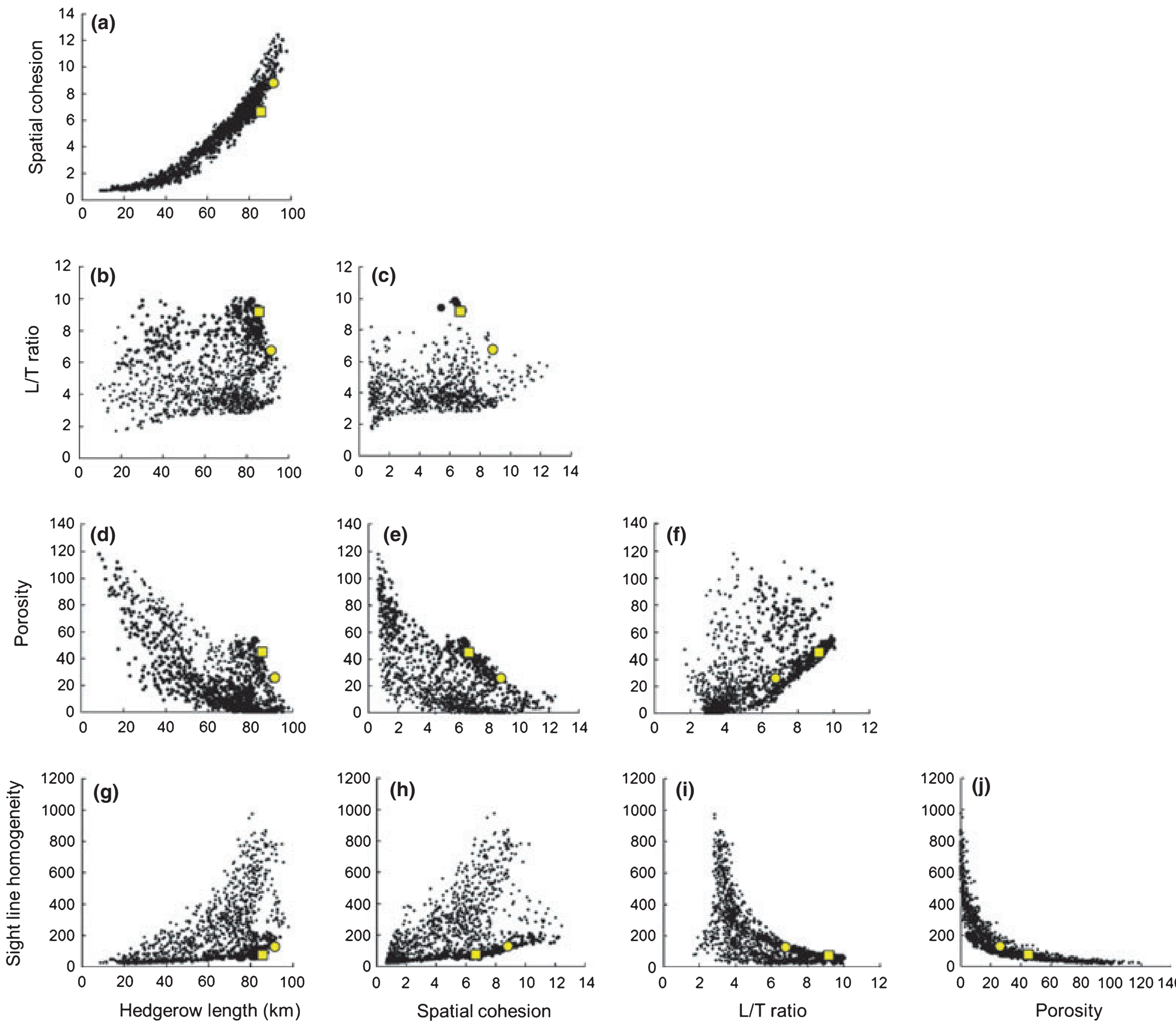

Fig. 2. The relations among five landscape objectives from a 7-dimensional solution space represented by 2-dimensional plots of relations between the objectives. Each point represents a landscape with a different hedgerow configuration. The objectives pertain to total linear network length (determining maintenance costs), spatial cohesion (determining ecological connectivity), the ratio between longitudinally and transversally oriented hedgerows bordering fields (L/T ratio, determining culture history value), the porosity of the landscape and the variation in sightlines (determining landscape perception). The original landscape (■, yellow) and the sketch design developed by a landscape management organization (•, yellow) are indicated. Adjusted from Groot, Jellema, & Rossing (2010).

alternatives within the solution space (Deb *et al.* 2002). Selecting solutions in less crowded areas promotes spread over the solution space (Fig. 1c), thus allowing more effective exploration of the solution space and fostering diversity of the generated alternatives.

Exploratory frameworks for spatial NRM planning based on these principles have been proposed and implemented in flexible software packages that can be configured to include new indicators in response to demands from the design process (Pressey *et al.* 2007; Groot *et al.* 2007; Holzkamper & Seppelt 2007; Daily *et al.* 2009; Scheller *et al.* 2010; Fürst *et al.* 2010). Visualization tools that can be operated by and with stakeholders support the learning and negotiation process (Kollat & Reed 2007; Castelletti, Lotov, & Soncini-Sessa 2010). Moreover, narratives that describe the sequence of events in their logical ordering to explain causes and effects simulated or projected by a model (Kay *et al.* 1999; Guhathakurta 2002; Walz *et al.* 2007; Cowling *et al.* 2008; Loupa Ramos 2010) may be a useful addition to computer-based and data-rich model outputs to explain solution spaces and the consequences of different solutions (Reitsma 2010). Recently, Vervoort *et al.* (2010) proposed a framework with criteria for the development of communication procedures to outline the properties, performance and the potential of adjustments to social and ecological dimensions of land-use systems. This framework proposes the use of diverse new and conventional media for visualization of results, including movies, web-based GIS, landscape visualizations and serious computer-based gaming in a participatory setting.

Illustration: planning of an ecological zone in a half-open hedgerow landscape

The evaluation of a landscape planning process for an ecological zone in an agricultural landscape presented by Groot, Jellema, & Rossing (2010) can serve as an illustration of creating diversity to explore the trade-offs and synergies among planning objectives. The reported project was conducted in cooperation with a provincial landscape management organization in the north of the Netherlands. The planning zone of *c.* 9 km^2 enclosed by (rail) roads was dominated by grassland fields of intensively managed dairy farms. These fields were surrounded by hedgerows that gave the landscape a half-open character, with variation in so-called sightlines, i.e., the distances visitors can see through the landscape without interference by landscape elements (cf. Fisher 1996). The porosity of the landscape was defined as the frequency of sightlines through the whole landscape, from road to road. The historical development of the region had resulted in fields that were stretched in one direction, with hedgerows predominantly placed longitudinal (L) to the field orientation, and less in the transversal (T) direction, resulting in a high L/T ratio. The hedgerows constituted an important habitat for many plant and animal species, and the ecological quality of which was expressed in the spatial coherence or connectivity of the landscape (Urban & Keitt 2001; Bennett, Radford, & Haslem 2006; Bodin & Norberg 2007).

The landscape management organization had planned new hedgerow plantings in the zone in a sketch design that was formulated on the basis on their extensive knowledge of the ecology and history of the region. This plan and the original situation were evaluated in an interactive process, using an exploratory modelling approach that generated a large Pareto-optimal set of landscapes that performed differently in terms of seven objectives that were identified in negotiation with the landscape managers: maximization of spatial coherence, L/T ratio and variation in sightlines, minimization of porosity, total length of the hedgerow network (as a proxy for maintenance costs), and the required planting or removal of hedgerows to realize a plan (as a proxy for implementation costs). The resulting solution space with alternative hedgerow configurations in the agro-landscape is presented in Fig. 2 for a subset of five objectives. The Figure shows that at the same level of performance of any of the objectives many alternatives are possible that perform better than the original situation and the sketch design. However, a detailed analysis showed that solutions that performed better for all the objectives simultaneously were very scarce, so that compromises would be needed. Gains in one objective are associated with sacrifices in other objectives; the extent of which is revealed by the trade-offs in the panels in Fig. 2. Such outputs may contribute to the understanding of the system by the stakeholders and can provide a sound basis for balanced decision-making that does justice to the perspectives and interests of broad groups of stakeholders, which is considered instrumental for active management of ecosystem services (Robertson & Swinton 2005). The landscape managers considered the application of the modelling framework to be supportive in their landscape redesign practice as was apparent from statements and from their continued participation in the 3-year research process. The need in exploratory models to define explicitly objectives and indicators brought out the largely implicit design rules of the landscape managers and stimulated reflection.

From diversity to a desirable future

Ultimately, after exploration of the available choices and their consequences, decisions need to be made on which alternative is most desirable. The indicators that describe the ecosystem services based on scientific approaches may be technical and complex in nature. For nonscientist stakeholders such as citizens, resource managers and policy makers, these indicators may not relate to their perception of and needs for certain ecosystem services. Indicators may be weighed based on multicriteria decision techniques to translate the multitude of science-based indicators into the set of indicators that describe more directly the demand for ecosystem services of a stakeholder group or society at large.

In industrial design, the indirect elucidation of demands of costumers has proven to be highly useful in strategic planning (Govers 1996). Demands are derived from interviews or surveys and expressed in stakeholders' statements. These statements are then related to the science-based indicators by multicriteria techniques such as quality function deployment

(Akao 1988) and analytic network process (Saaty 1996) based on the judgments of an expert panel, as was demonstrated for agricultural land use (Parra-López *et al.* 2008). The resulting array of weights represents the interface between the demand for ecosystem services by the stakeholders and their supply as calculated using scientific knowledge captured in system models. Thus, NRM alternatives initially characterized in scientific terms are translated into terms relevant to participants in adaptive management–oriented projects.

Illustration: landscape services

Recently, Parra-López *et al.* (2008) proposed to assess ecosystem services provided by a landscape in terms of social benefit, calculated as the sum of private and public benefits. Private (market) benefits can be quantified as the financial returns to farmers arising from their farm management and are assumed to constitute one of the basic stimuli for farmers to adopt or reject a set of farm management practices. Public (nonmarket) benefits represent the market and nonmarket impacts for society in general associated with a set of farm management practices, such as biodiversity, amenity value of landscape but also public costs associated with subsidies.

In interaction with local stakeholders, Parra-López *et al.* (2008) identified salient economic and environmental objectives and used these to generate a diversity of landscape alternatives, ranging from least to most desirable using an evolutionary algorithm approach in combination with Pareto-based ranking. The solution set was then translated in terms of changes in private (ΔU_{PRV}) and public (ΔU_{PUB}) benefits compared to the current situation. In Fig. 3, the solution set of landscapes is represented schematically as an ellipse, with the current landscape in the origin and the axes representing the change in private (ordinate) and public (abscissa) benefits. Each ellipse thus comprises a set of discrete solutions or landscape configurations, similar to the results presented in Fig. 2. The landscape with the greatest social benefit was identified graphically by moving the line $y = -x$ outwards, until it meets the last point (i.e. landscape) in the ellipse, as schematized in Fig. 3a. Combining the solution space of Fig. 3a with the policy design framework of Pannell (2008) allowed the determination of appropriate policy instruments to encourage the implementation of a desirable alternative or to avoid the implementation of an unfavourable alternative (Parra-López *et al.* 2009). For instance, alternatives located in the part of the solution space that is in area A in Fig. 3a provide large public benefits at the expense of private benefits of the landholders. Implementation of such alternatives could be stimulated by subsidies to the landholders. On the other hand, alternatives in area D are characterized by high private benefits that are detrimental to the public benefit and should therefore be discouraged by taxes equivalent to the gain that the landholders obtain by adopting such an alternative. Alternatives in area B, which also harbours the social optimum, have a positive effect on both private and public benefits. Lack of interest among stakeholders in one of these alternatives may point to lack of awareness or knowledge. Extension mechanisms such as technology transfer, education, communication, demonstrations and support for community networking could be appropriate in such a case. Lack of interest may also mean that the scientific

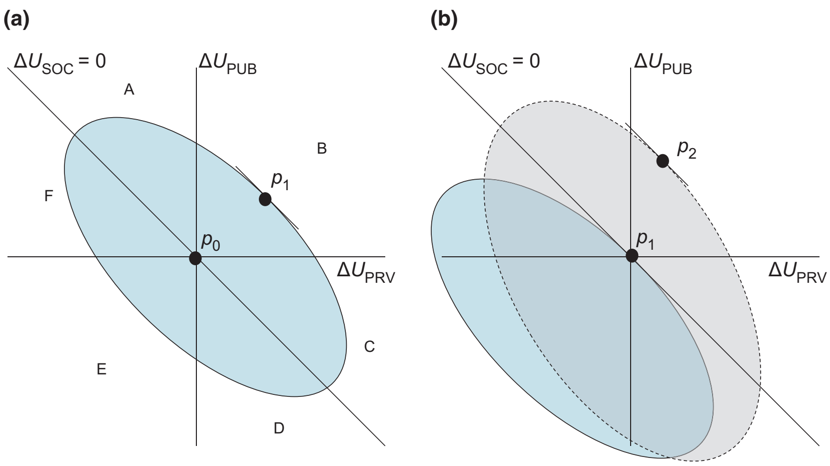

Fig. 3. (a) The solution space (blue shaded) of alternatives expressed in terms of change in net benefit or utility (ΔU) relative to the existing situation (p_0). The solution space delineates a set of discrete alternatives (i.e. landscapes in the example in the text). The areas separated by the lines $x = 0, y = 0$ and $x = -y$ form areas where different policy mechanisms are suitable to reach a desired alternative or to avoid an undesired alternative. The areas differ in the change in private landholder net benefit (ΔU_{PRV}), public net benefit (ΔU_{PUB}) and social net benefit ($\Delta U_{SOC} = \Delta U_{PRV} + \Delta U_{PUB}$), following Pannell (2008): A. Positive incentives through financial or regulatory instruments to encourage change; B. Extension by technology transfer, education, communication, demonstrations, support for community networking; C. No action (informed inaction); D. Negative incentives by financial or regulatory instruments to inhibit change; E. No action (informed inaction); F. Technology development by development of improved land management alternatives, such as through strategic R&D, participatory R&D with landholders, provision of infrastructure to support a new management alternative (Parra-López *et al.* 2009). The point p_1 indicates the social optimum in graph (a). (b). Situation reached after implementation of the solution of point p1 in graph (a), the original solution space (blue shaded) and a new solution space (grey shaded) as determined by changes in the system and its environment. The point p_2 indicates the social optimum in graph (b).

representation of reality is falling short in important components, pointing to the need for redefinition of the problem.

Perpetuating the cycle

After implementation of the selected alternative, an adaptive management approach can be adopted for further fine-tuning to the context of the local environment and for dynamic adjustment of landscape management to environmental changes and natural processes. If an efficient exploratory framework for generating, evaluating and selecting NRM alternatives is in place, the adaptive management of the system can be supported by repeated design cycles. In a new planning cycle, the system and its environment will have changed, for instance, in terms of goals and social preferences, in bio-physical environment, because of technological and socio-institutional innovations, etcetera. This will affect the shape of the solution space in the next design cycle. This is schematically demonstrated in Fig. 3b, which illustrates the selection of the optimum solution in two consecutive design cycles.

Conclusion

The practice of developing 'sketch designs' or a small number of scenarios appears to be counter to the need for learning and negotiation as part of NRM design projects. Science-supported design processes can explore a rich diversity of NRM alternatives to foster negotiation and learning. Prioritization of perspectives and weighing of objectives should be postponed until after such exploration. Methodological approaches involving evolutionary heuristics, Pareto-based ranking procedures and multicriteria decision methods from the domain of industrial design provide the means to generate, evaluate, select and present sets of NRM alternatives and for interfacing science-driven and society-driven indicators. These methods harbour unused potential for application in ecology and land-use planning.

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